

# Non-Contact versus Contact-based Sensing Methodologies for In-Home Upper Arm Robotic Rehabilitation

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**Abstract**—In recent years, robot-assisted rehabilitation has gained momentum as a viable means for improving outcomes for therapeutic interventions. Such therapy experiences allow controlled and repeatable trials and quantitative evaluation of mobility metrics. Typically though these robotic devices have been focused on rehabilitation within a clinical setting. In these traditional robot-assisted rehabilitation studies, participants are required to perform goal-directed movements with the robot during a therapy session. This requires physical contact between the participant and the robot to enable precise control of the task, as well as a means to collect relevant performance data. On the other hand, non-contact means of robot interaction can provide a safe methodology for extracting the control data needed for in-home rehabilitation. As such, in this paper we discuss a contact and non-contact based method for upper-arm rehabilitation exercises that enables quantification of upper-arm movements. We evaluate our methodology on upper-arm abduction/adduction movements and discuss the advantages and limitations of each approach as applied to an in-home rehabilitation scenario.

**Keywords**—robotic rehabilitation, vision-based assessment, EMG measurements, therapeutic robotics

## I. INTRODUCTION

Rehabilitation therapy can be a very practitioner intensive process. When patients enter into the process they are often required or asked to perform exercises at home in-between their clinical visits. Proper compliance is strongly correlated with shorter time to recovery as well as reduction of pain in the long term (Wakiji, 1997). During the time between therapy sessions there are many factors which affect patient compliance, including forgetfulness, lack of motivation, boredom, and lack of instant feedback. To deal with these issues, researchers have shown the positive use of robots in assistive therapy applications ranging from stroke rehabilitation (Krebs et al, 1998; Volpe et al, 2000; Burgar et al, 2000; Lum et al, 2002; Hesse et al, 2003; Reinkensmeyer et al, 1999; Loureiro et al, 2003; Patton and Mussa-Ivaldi, 2004) to motor development in children (Galloway et al, 2008). In this venue, robotic systems for contact-based rehabilitation have generally been used to objectively assess the performance of a patient through repeatable and quantifiable metrics, as an effective means for rehabilitation (Colombo et al, 2005).

For in-home rehabilitation however, exercise may not be performed as well or at the frequency necessary for optimizing the therapy intervention. As such, two key components necessary to promote adoption by both the clinicians and patients are the inclusion of technologies for 1) maintaining patient motivation outside of the clinical setting and 2) monitoring and measuring movements in the home environment (Eggleston et al, 2009). Using robotic systems that employ non-contact approaches can provide a mechanism for instituting safe in-home upper limb rehabilitation techniques that address these two needs. However, in the rehabilitation domain, there are limited efforts that use robotic systems that employ non-contact approaches. Those systems that exist have typically focused on social interaction, whereas the objective is to maintain engagement with an exercise protocol through hands-off interaction strategies (Fasola and Mataric, 2012). Although these efforts show the effective use of a socially assistive robot to maintain motivation for exercise, such systems have not focused on the criteria needed for measuring information with respect to the clinical objectives, i.e. quantifying the movement characteristics necessary for objective performance assessment.

As such, in this paper, we discuss both a contact and non-contact based sensing method for extracting upper-arm movement characteristics through robot interaction. In Section 2, we discuss a non-contact method that uses vision-based techniques to extract arm movement data whereas Section 3 discusses the physical contact method, which utilizes EMG sensors coupled with a Hidden Markov Model (HMM) algorithm to extract movement parameters. We compare these two approaches in Section 4 using data extracted from subjects' performance on three upper-arm exercise motions: shoulder flexion, elbow flexion, and arm extension. We then provide observations and concluding remarks in Section 5.

## II. NON-CONTACT METHOD FOR UPPER-LIMB MOVEMENT EXTRACTION

In this section, we discuss a methodology to extract upper-arm movement metrics based on a non-contact method that uses off-body camera data. In this approach, several image-processing techniques are employed. First, a recorded video sequence of the user's exercise motions is translated into a

unified gray-scale image that captures the full time-sequence of exercise movements. This is accomplished via a process called Motion History Imaging (MHI). Next, a contour extraction process is applied to the MHI image for providing a geometric representation of the movements. Finally, a method called Random Sample Consensus is applied to the representative contour, which enables the determination of straight-line segments used to calculate specific movement parameters, i.e. arm joint angle positions.

#### A. Representing Exercise Movements in a Video Sequence

The initial step in quantifying the subject's movements is to segment a video sequence into a unified representation that contains pertinent information with respect to the overall movement sequence (Brooks and Howard, 2009). To perform this operation, we utilize a methodology called Motion History Imaging (MHI), which computes a static image template where pixel intensity is a function of the recency of motion in a sequence (Bobick and Davis, 2001). A single image thus can be constructed that contains the necessary information for determining how a person has moved during an exercise sequence. In an MHI, pixel intensity is a function of the motion history at that location, where brighter values correspond to more recent motion. We currently use a simple replacement and linear decay operator using the binary image difference frames (Equation 1). Examples of MHIs for an elbow flexion exercise are shown in Figure 1.

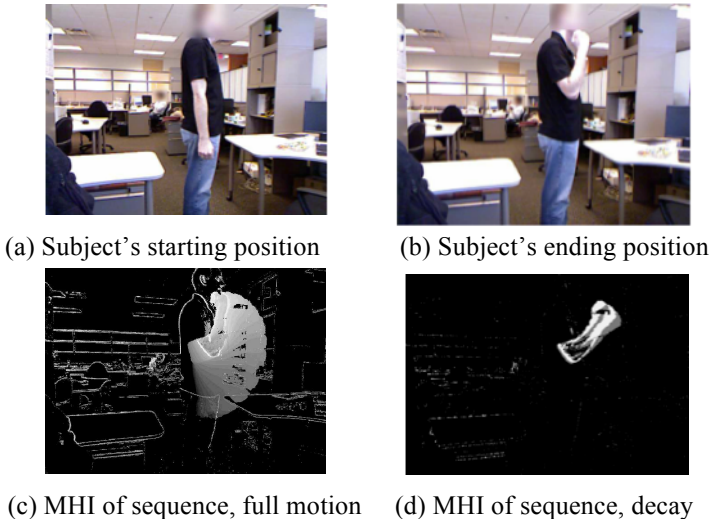


Figure 1. Motion History Images of an elbow flexion exercise

$$H_t(x, y, t) = \begin{cases} \tau & \text{if } D(x, y, t) = 1 \\ \max(0, H_t(x, y, t-1) - 1) & \text{otherwise} \end{cases} \quad (1)$$

where  $H_t(x, y, t)$  represents the MHI function,  $D$  is a binary image sequence indicating regions of motion,  $x$  and  $y$  are the horizontal and vertical directions in the image, respectively,  $t$  is the current time step, and  $\tau$  is the current intensity value.

#### B. Creating a Geometric Representation of the Movement

Once the patient's movements have been captured, a contour representing the shape of the respective movements is computed in order to construct a geometric representation of the exercise. We first utilize a median filter to remove smaller, unwanted contours in the image typically caused by camera jitter or movement of body parts other than the desired limb. For our purposes, the median filter used is a sliding-window spatial filter that replaces the center pixel value in the window with the median of all the pixel values in the window (Figure 2b). After filtering out smaller contours, a canny edge detection algorithm (Canny, 1986) is used to compute the edges of the contour and the convex hull of the edge-detected image is determined (Figure 2c). By looking at three consecutive vertices of the convex hull, which can be represented by a polygon, the resulting angle between the three vertices is classified as concave or convex. The output from this methodology provides an ideal geometric outline representing the time-sequence of movement during an exercise scenario (Figure 2d).

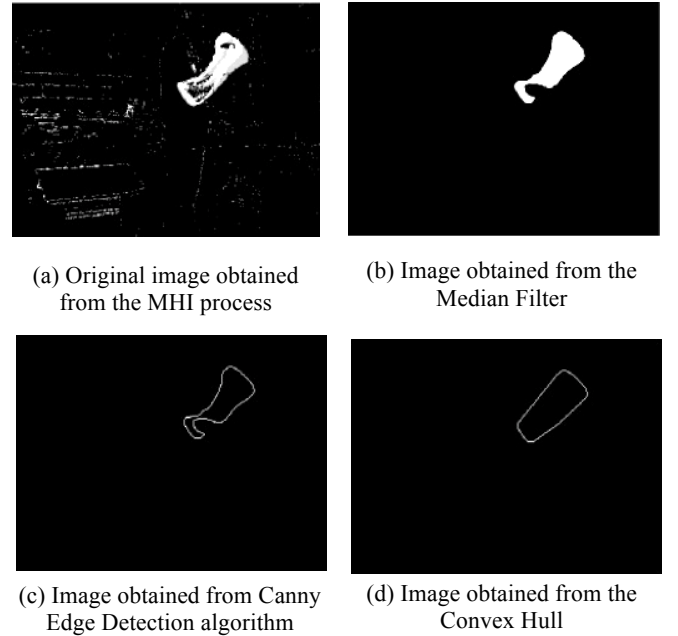


Figure 2. Example image processing sequence used to extract human exercise movements

#### C. Computing Joint Angles Related to Exercise Movement

Given the geometric representation of the exercise movement, we now determine relative joint angles associated with a moving body part. Given that our contour (i.e. convex hull) as discussed previously represents a time-sequence of limb movements for an exercise, if we determine the relative angles between the upper and lower lines of the contour, we can compute the relative angle associated with the primary joint movement. For example, during a shoulder flexion motion, the arm rotates around the shoulder joint. Our methodology would determine the range of motion (i.e. the relative joint angles) of the shoulder joint, which would be the primary joint contributing to this exercise. For calculating this

parameter, we utilize the Random Sample Consensus (RANSAC) algorithm (Chum, 2005; Fischler and Bolles, 1981) which determines the best possible line fit given a sample set of points by iteratively selecting a random subset of inlier points from the original input data set that is consistent with a line-model of unknown parameters. The algorithm can be described mathematically as follows: Let  $P$  be the probability that a sample of size  $m$  is randomly selected from a set  $U$  of  $N$  data points

$$P(I) = \frac{\binom{I}{m}}{\binom{N}{m}} = \prod_{j=0}^{m-1} \frac{I-j}{N-j} \leq \epsilon^m, \quad (2)$$

where  $\epsilon$  is the fraction of inlier points  $\epsilon = I/N$ . The number of inliers  $I$  is not known beforehand. The system continuously finds sample sets of inlier points until the likelihood of finding a better model given a different set of inliers falls under a predefined threshold. The outcome of this process is a set of points that define the upper and lower bounding lines of the convex hull.

Once the points that create the upper and lower lines are recognized, the slopes of each are used to calculate the angle between the two lines via simple geometry as shown in Equation 3

$$\begin{aligned} m_1 &= \frac{y_2 - y_1}{x_2 - x_1} \\ m_2 &= \frac{y_4 - y_3}{x_4 - x_3} \\ \Theta &= \arctan\left(\frac{m_2 - m_1}{1 + m_2 m_1}\right) \\ ROM &= \left| \Theta - \frac{180^\circ}{\pi} \right| \end{aligned} \quad (3)$$

where  $x$  and  $y$  are the coordinates of points on each line segment,  $m_1$  and  $m_2$  are the slopes of each line, and  $\Theta$  and ROM are the current angle in radians and degrees, respectively. The maximum angle found over the length of the video sequence gives the Range Of Motion (ROM) (i.e. maximum joint angle measurements) of the subject's movements. The ROM correlates to the bounded movement of the primary joint involved in the exercise movement. In Section 4, we will discuss results achieved from applying this non-contact methodology to extract joint angles associated with three upper-arm exercises performed by different human subjects.

### III. CONTACT-BASED METHOD FOR UPPER-LIMB MOVEMENT EXTRACTION

One method for contact-based rehabilitation is the utilization of an upper extremity robotic orthosis. A common method used for orthosis control is to use bio-signals extracted from EMG signals. As such, for extracting upper-arm movement metrics in this work, we utilize a statistical modeling approach that incorporates EMG signals for recording of muscle activity level. In this method, a Hidden Markov Model (HMM) process is used to predict the hidden sequence of states (i.e. upper extremity motions) by only evaluating a set of observations (i.e. associated EMG activity). EMG signals, which represents the electrical activity that

occurs when skeletal muscles expand and contract, have been shown to be essential in the myoelectric control of artificial/prosthetic limbs (Asghari Oskoei and Hu, 2007, Kiguchi and Fukuda, 2004). EMG signals provide pertinent information on the desired intent of muscle exertion as well as the types of motions the arm is commanded to perform. By observing a sequence of EMG signals extracted from muscles involved during upper-arm reaching motions, the HMM process can predict the actual joint angles related to the movement being performed (e.g., the joint angles of the elbow and shoulder). The Range Of Motion (ROM) metric associated with the joint angles derived from the contact-based method correlates to the summation of the elbow plus shoulder angles involved in the movement. In this research, the sequence of EMG signals correspond to observations the HMM will use as an input while the joint angle positions are the sequence of states the algorithm will output.

#### A. Acquiring the EMG data signal

To implement the HMM algorithm described in this work, a data acquisition system capable of simultaneously capturing a subjects EMG activity during upper-arm motions and the joint angle information associated with those motions is utilized. The Upper Extremity Motion Capture System (Figure 3) was used for this purpose (Nanda et al, 2009). The system consists of a platform for stability and an upper-arm brace that constrains the arm to three degrees of freedom.

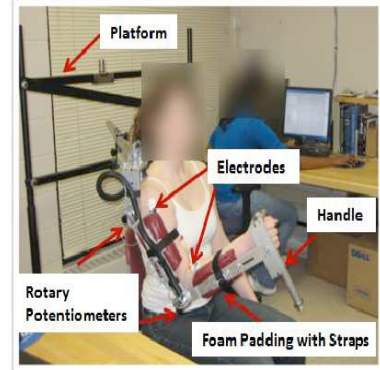


Figure 3. Upper Extremity Motion Capture System

Joint angle measurements are taken through the use of three rotary potentiometers that are integrated in the brace: two at the shoulder joint, and one at the elbow joint. Each potentiometer has a voltage range of  $\pm 2$  volts, corresponding to joint angles between  $0^\circ - 360^\circ$ . The top shoulder joint is configured to collect data from  $0^\circ - 140^\circ$  in the transverse plane, while the side shoulder joint collects data in the sagittal plane within the same range. The elbow joint can measure between  $17^\circ - 180^\circ$  in the sagittal plane. EMG data is recorded through the use of dual EMG electrodes with two snaps and two gel sites separated by 1 cm. Both EMG and angle measurements are sent to the BioRadio™, a lightweight, commercial bioinstrumentation system with 12 configurable channels from Cleveland Medical Devices (Cleveland Medical Devices, 2008). Data from this system can be acquired at a frequency of 960Hz with 12 bits data rate. The first two channels of the BioRadio are configured to accept the potentiometers data

whereas the next four channels are set to collect EMG signals from the deltoid, the biceps brachii, the triceps brachii, and the brachioradialis.

### B. Hidden Markov Model

Since EMG data tends to be large and usually contains redundant information, the data is first transformed into a representative set of features to reduce the amount of data under analysis without compromising the information it contains. Since EMG signals are continuous, the data also needs to be quantized in order to be processed as a discrete signal. Hence, a feature extraction approach is performed on the raw EMG data, followed by a vector quantization method, before it is used as input into the HMM process. As suggested by Oskoei (Asghari Oskoei and Hu, 2007), the EMG signal is decomposed into segments of 100 data points. Features are then extracted using a fourth order autoregressive model, which collects the first four coefficients from each channel and then feeds the extracted features into a vector quantization process using the K-means algorithm. These features, which represent the contact-based input signals, are then parsed into a Hidden Markov Model.

A Hidden Markov Model (HMM) is defined by the number of states  $M$ , the number of observations  $N$ , the transition matrix  $A$  which signifies the probability of the transition from one state to another, the emission matrix  $B$  which corresponds to the probability of an observation occurring given a state, and the initial state distribution,  $\pi$ . These parameters are represented by a compact notation,  $\lambda$  (Chan and Englehart, 2005):

$$\lambda = (\pi, A, B|M, N) \quad (4)$$

In order to define all the necessary parameters of our HMM, three basic tasks need to be performed. The first task, evaluation, is to calculate the probability of the sequence of observations corresponding to the specific HMM parameters. The second task involves the discovery of the sequence of states that generated the corresponding observations. This is referred to as the decoding stage, and the Viterbi algorithm is used to perform this task. Lastly, the third task is to adjust the model parameter,  $\lambda$ , in order to maximize the probability of a sequence of observations fitting a model. This stage is called the learning stage (Rabiner, 1989). For our application, observations are associated with the quantized EMG signal and the state represents joint angle measurements. This approach is an extension of previous work shown in (Nanda et al, 2009). Through this process, given a sequence of EMG signals, which are directly correlated with muscle exertion during an arm exercise motion, we can extract the corresponding arm joint angles of the user.

## IV. EXPERIMENTAL PROTOCOL

In this section we compare the two approaches for extracting arm movement data based on an experimental protocol that recruited five human subjects. Subjects ranged in age from 17 to 24, and consisted of three males and two females. Subjects were required to perform three different motions: shoulder flexion, elbow flexion, and arm extension

(Figure 4). Shoulder flexion consists of keeping the entire arm straight and rotating it about the shoulder joint in the sagittal plane. Elbow flexion corresponds to the flexion or the curling of the arm at the elbow joint. Arm extension is a combination of shoulder and elbow flexion performed in the sagittal plane. Subjects begin this motion starting from the 90° elbow joint angle and then reaching forward in the sagittal plane.

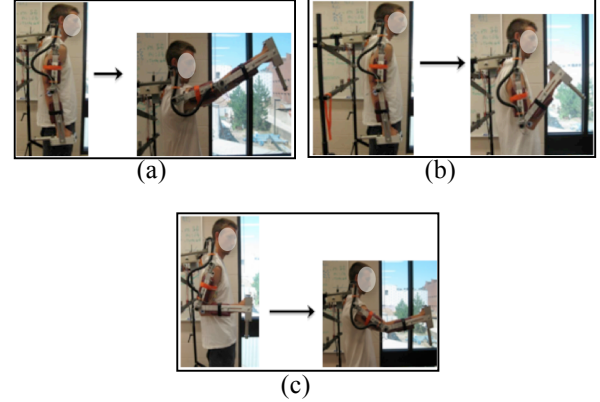


Figure 4. Upper-Arm Exercise Motions: (a) Shoulder Flexion, (b) Elbow Flexion, (c) Arm Extension

For the non-contact based method, a Logitech webcam with a 15 frame per second (fps) frame rate was used to capture the motion of each subject. For the contact-based protocol, the Upper Extremity Motion Capture system with a data acquisition rate of 960Hz with 12 bits data rate was used in conjunction with the CaptureLite software from Cleveland Medical Devices to extract the data associated with the exercise movement.

For each motion, subjects were asked to perform three trials of thirty-second long repetitive and continuous arm actions. The results from each algorithmic approach (non-contact versus contact) were plotted against the actual joint angle measurements to evaluate its accuracy. Figure 5 highlights an example result from the contact-based approach derived from a shoulder flexion exercise of one subject whereas Figure 6 highlights an example result for the non-contact based approach derived from an arm extension motion.

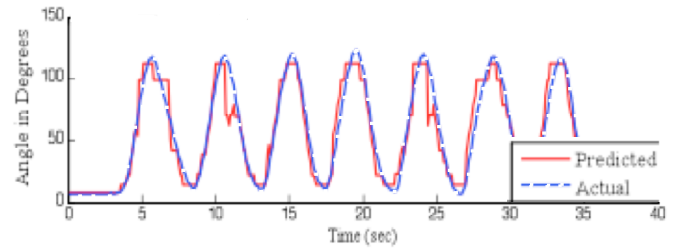


Figure 5. Extracting movement data from a shoulder flexion exercise using the contact-based approach



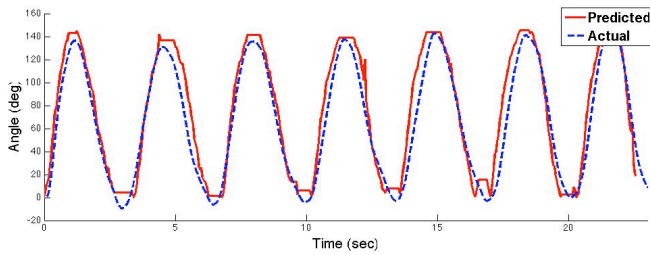


Figure 6. Extracting movement data from an arm extension exercise using the non-contact based approach

To evaluate each algorithm, the average error between the predicted and actual angle measurements for the primary joint of motion was calculated (Figure 7). With overall mean errors of  $14^\circ$  and  $13^\circ$  for the contact-based and non-contact based algorithms respectively, both options seem viable for calculating subject movements during robot-assisted rehabilitation. As a comparison, the work presented by Au and Kirsch (Au and Kirsch, 2000) yielded an error less than  $20^\circ$ . The largest error in both the contact-based approach (as well as the work by Au and Kirsch) was found during elbow flexion motions. Whereas, the largest error for the non-contact based approach was found during the arm extension motion.

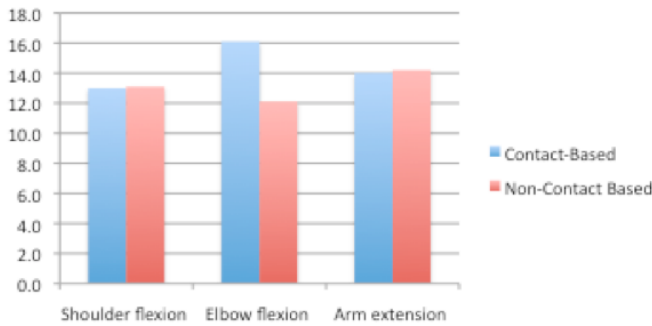


Figure 7. Error Analysis for Range of Motion (ROM) associated with Exercise Movements from the five human subjects.

## V. DISCUSSION AND FUTURE WORK

Given that both methods perform reasonably well, in this section, we discuss the pros and cons of each method for developing a set of criteria that can be used for determining which to employ in a rehabilitation scenario. The main issue in the development of a contact-based approach is the requirement for a calibration routine. In the case of the HMM method, this required access to EMG sensors that could be used for learning of system parameters. For the non-contact based approach, there is a need to have movement be in-line of site of the camera viewpoint. In other words, if the camera cannot image the full motion of a joint, an invalid angular value will be derived. In general, the contact-based approach provides a more robust model for generalizing the tracking of joint angles since by utilizing multiple EMG sensors, detailed information about the patient's muscular activity can be extracted and utilized for tracking more complicated movements without requiring a change in the algorithm itself. For the non-contact based approach, a new model would need to be created for more complicated motions in which multiple

joints move simultaneously in different planes (e.g. sagittal versus transverse plane). However, for simple motions, which require only one joint to move significantly, the vision-based approach allows for quick and reliable calculations with minimal cost. In terms of the feasibility for patients being able to obtain each device for personal use though, the non-contact based approach seems to provide a more viable option. The contact-based approach, although more robust, requires an integrated hardware system that would be challenging to integrate safely for in-home use. However, it is ideal for rehabilitative facilities requiring such devices. In contrast, the non-contact based approach is a cost efficient method for in-home rehabilitation. With the availability of a simple camera, a patient could perform rehabilitative exercises at home and have the results sent to his or her physical therapist for analysis.

As such, the future objective of this work is to robustly quantify physical rehabilitative metrics for patients during in-home therapeutic sessions with an assistive robotic device providing guidance. In the immediate future, we will look at other mobility metrics, such as velocity and jerkiness, in order to obtain a more detailed assessment of patient movement history. Acceleration would be of particular importance because it can be used to measure the spasticity of certain patients, such as those diagnosed with cerebral palsy.

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